How the Mighty Have Fallen: An Examination of Factors Into Restaurants Closing in Las Vegas

Yuqing (Candice) Zhang

Abstract

In this research, I examined how do the mechanisms of ‘Food’, ‘Location’, and ‘Service’ might lead to restaurant closing in Las Vegas. Contrary to the common belief, this study shows that ‘Service’ is actually not a significant factor when predicting restaurant closing in the Las Vegas area. Instead, by applying a Generalized Linear Model, I found that ‘Food’ and ‘Location’ have more weights in determining whether a restaurant would close or not. In addition, results from performing a sentiment analysis on Yelp reviews also shows that customers wrote more positive reviews for open restaurants than for closed restaurants, under all of these three predictors.

Humans are innately pleased by good food and unique dining experiences. The National Restaurant Association showed that in 2005 (the latest year for which the statistics were available), the average household expenditure for restaurant food was $1,054 per person, or $2,634 per household (Sandlin, 2005). These numbers make owning a restaurant a good business opportunity for aspiring food-service entrepreneurs, even during economic slowdowns and when consumer prices are rising. On the other hand, the restaurant industry has always been among the most competitive and challenging ones to navigate through, and failures are nothing new. However, the struggles have left some wondering what is behind the phenomena of restaurant closing. Nonetheless, there have been many articles talking about the determining factors of businesses' success, though not much has been done on researching why businesses fail. The purpose of this study is to examine factors of restaurants closing. This study will build on three previous studies on restaurant failure rates (e.g., Parsa et al. 2005) that have debunked the myth that nine out of ten restaurants fail in the first year. Building on the previous findings, instead of adopting traditional approaches, such as interpersonal interviews or surveys administrations, in my study, I will take on a different method to study why restaurants close by performing a detailed text analysis on Yelp reviews.

With more and more access and ease in using the Internet, an increasing number of people are writing reviews for their experiences (Hu, Liu, 2004). As a result, the number of reviews that a product receives grows rapidly over the recent years. Some popular products can get hundreds of reviews instantly at some large merchandise sites, providing cascades of complex information. In addition, many reviews are long and heavy on anecdotes, with only a few sentences containing actual opinions on the product. With these features, therefore, if something goes wrong, the large quantity of review information makes it very difficult for product manufacturers to keep track of customer opinions of their products. On this front, there hence is a need to classify reviews into categories and analyze them accordingly. In this project, I study the problem of generating feature-based summaries of customer reviews of restaurants. Here, features broadly mean restaurants attributes and functions. Although the determinants of business failure are multidimensional, I focus on examining three main factors, food, location and service.

Reasons for Business Failure

Failure in the restaurant industry was studied by Parsa et al. (2005). They listed three key factors as contributing to restaurants closing: size and type of operation, competition and restaurant concept or segment. The second factor, restaurant concentration, emerged from the finding that restaurant failure rates are higher in U.S. Postal ZIP codes where there is a high concentration of restaurants. This extended to downtown locations, which had far higher restaurant failure rates compared to suburban locations. Parsa and colleagues (2005) also interviewed several owners of failed restaurants and then highlighted personal reasons for restaurant failure. Factors included a high "demand of labor and time, poor food-quality controls or low perceived value, being undercapitalized or having poor financial management, and the quality of employees and service". Their results showed that location, as well as service are two important factors contributing to restaurant closing.

In addition, food is at the soul of a restaurant and plays a crucial role in restaurants success. Therefore, apart from the two aforementioned factors, I added a third factor, food as a critical element to examine as well. In all, my first hypothesis is thus formed as:

Hypothesis 1: Food, location and service are significant predictors in facilitating restaurants' continuation in business.

Sentiment Analysis

My approach in this project bears many connections with Dave, Lawrence and Pennock's work on semantic classification of reviews. Using available training corpus from several websites, where each review already has a class (e.g., thumbs-up and thumbs-downs, or some other quantitative or binary ratings), they designed and experimented a number of methods for building sentiment classifiers. They showed that such classifiers perform quite well with test reviews (Dave, Lawrence & Pennock, 2004). My approach differs from theirs in two main aspects: (1) my focus is not on classifying each review as a whole but on classifying each sentence in a review. Within one piece of review, some sentences may express positive opinions about certain product features, while some other sentences may express negative opinions about some other product features; (2) they did not mine product features from reviews on which the reviewers have expressed their opinions. Treating each sentence instead of each review as an analysis unit will increase the accuracy of the estimated model. More specifically, I expect to find the following result with my analyses:

Hypothesis 2: Under each predictor, businesses that are still open received higher sentiment score than businesses that are close.

Method

Data. Currently, Yelp is the most popular online consumer review website used for local business reviews and recommendations (Bird, 2015). It is an online consumer review website for shopping, restaurants, home and other services containing more than 83 million reviews (Yelp, 2016). The abundance of Yelp reviews provides sufficient starting point for doing text analysis. This year, Yelp presents the ninth round of its own dataset challenge. Yelp released a dataset that includes information about local businesses in 11 cities across four countries. All data were enclosed in five *json* files. For my own convenience, I converted all the *json* files to *csv* format files. In my project, I used the sub dataset that only contains text reviews for businesses to explore the interplay of my three matters of interest on restaurant closing. After filtering to include only reviews from Las Vegas restaurants, my data contains 64,991 reviews of 1,645 closed restaurants and 568,433 reviews of 4,090 open restaurants.

Procedures. Figure 1 shows the architectural overview of my opinion summarization system. The input to this system is a *json* file containing each piece of review that Yelp provides, and the output is a sentiment score under each of the three predictors (i.e. food, location and service) for each open/close restaurants in Las Vegas in each year from 2012 to 2016.

[FIGURE 1 ABOUT HERE]

The system performs the summarization in four main steps: (1) filtering the raw reviews from Yelp so that we only analyze reviews within our matter of interest; (2) identifying features of the product that customers have expressed their opinions on, and finding out those sentences that talking about location, food or service; (3) for all sentences under one feature, calculating a sentiment score; and (4) producing a summary using the discovered information. More details for each step are discussed below.

1. Filtering

Filtering was performed on the businesses so that I only include the restaurants in the Las Vegas area. Using the *is_open* variable in the original dataset, I further split the restaurants into open (*is_open* = 1) and closed (*is_open* = 0) restaurants for further comparisons. After the filtering process I had two data files, one with 64,991 pieces of reviews of 1,645 closed restaurants, and the other with 568,433 reviews of 4,090 open restaurants. Following analyses were done separately for each of the two data files.

2. Feature Sentence Extraction

2.1 *Word Bank*. In order to extract sentences about either food, location or service, I utilized the Corpora project (Corpora Project, 2016) from the GitHub, as well as the Thesaurus website to find words that pertain to these three features. I note here that Corpora is a collection of static corpora of words. For example, some of the words that related to food are given as follows: *food, bread, cooking, cuisine, drink, foodstuff, meal, pizza.*

2.2 *Part-of-Speech Tagging (POS).* Product features are usually nouns or noun phrases in review sentences, so the part-of-speech tagging is crucial. My POS tagging comes from the Natural Language Tool Kit. I used the NLProcessor linguistic parser (NLTK, 2000) to parse each review to split text into sentences and to produce the part-of-speech tag for each word (whether the word is a noun, verb, adjective, etc). Some pre-processing of words was also performed, including removal of stop words, stemming and fuzzy matching

2.3 *Feature Sentence Extraction*. I then extracted all the nouns (‘*NN*’ or *‘NNJ’*) out of the sentences. If any of the nouns in the sentence contains words from any of the feature word banks, the sentence will be included in that category. For example, the sentence “The lettuce in that ice berg salad is so fresh!” will be added to the ‘Food’ category. After this task, I collected all sentences under each of the three categories for every restaurant.

3. Sentiment Analysis

NLTK has some built-in utilities for doing sentiment analysis. For this task, I used their sentiment analyzer function to calculate a score for every sentence under each feature, for every restaurant (Hutto&Gilbert, 2014). Then I took the mean of the sentences’ scores and output it as the sentiment score for that specific category of the restaurant.

4. Summary Generation/Analysis

Previous steps were performed for each individual year from 2012 to 2016. For each year's data the calculations were done separately for open and close restaurants for further comparisons. To investigate *Hypothesis 1*, I fitted a Generalized Linear Model (a logistic regression) to my outputted scores, with the three features as explanatory variables and whether the restaurant close or not (open = 1, close = 0) as the response variables. Coefficients were calculated to find significant factors leading to restaurant closing. To investigate *Hypothesis 2*, I compared the mean sentiment scores of all three features for both open and close restaurants in each year.

Results

Table 1 displays the descriptive statistics: Number of observations, minimum, standard deviation, mean, and maximum values for the sentiment scores under three predictors from year 2012 to 2016 were presented.

[TABLE 1 ABOUT HERE]

Figure 2 shows the mean ratings for open and close restaurants accordingly. It is clear that the restaurants that are open received consistently higher rating than those that are close.

[FIGURE 2 ABOUT HERE]

Application of GLM Model

A logistic regression model was adopted to test for *Hypothesis 1*, to examine whether food, location and service are significant predictors in facilitating restaurants' continuation in business. I combined together the sentiment scores throughout the five years under the three predictors for the model fitting. Food, location and service served as the explanatory variables, and whether the restaurant is open or not as the binary outcome variable. The result partially supported *Hypothesis 1.* According to the generalized linear model, only food and location are significant factors in predicting whether a restaurant would close or open. Summary of the model is shown in Table 2.

[TABLE 2 ABOUT HERE]

Open vs. Close Sentiment Score Comparison

To better understand the relationship between the sentiment scores drawn from the reviews for open and close restaurants, I plotted the mean of the scores under each category from year 2012 to 2016, to visualize and test for *Hypothesis 2*. Figure 3 shows the result. It is clear that under each predictor, restaurants that are still open generally received higher sentiment score than restaurants that are close, which is mostly consistent with *Hypothesis 2*.

[FIGURE 3 ABOUT HERE]

Discussion

In the analog age, collecting data about behavior—who does what when—was expensive. Now, in the digital age, the behaviors of billions of people are constantly being recorded, stored, and analyzable (Salganik, Bit by Bit). The ever-rising flood of big data means that we have moved from a world where behavioral data was scarce to a world where behavioral data is plentiful. In the past, although there has been some researches studying the various factors leading to business failure, previous approaches were not able to collect information of large amount of restaurant customers. Moreover, there is a lack of concrete proof of predictive relationships between factors and restaurant closures.

In this study, I tackled both issues. First, I had business administrative records data that Yelp created and collected as part of their routine activities. Critically, these business administrative records are not just about online behavior. By doing text analysis, I was able to find the hidden sentiment of the reviewers. Second, large data sets greatly increase our ability to make causal estimates from observational data. I fitted a logistic regression model to the three predictors and found the significant factors. As a pioneer to apply this model to sentiment scores calculated from the reviews, my results partially confirmed the model that predicts food and location as two significant predictors in facilitating restaurants' continuation in business.

The results of this study suggest directions for further study on other factors, such as ambiance and price range, as well as between-factor interaction effects. In addition, it calls for analyses on the subsets of the data to add richness to my results. For example, previous studies confirmed that Mexican style restaurants reported the highest failure rate, followed by sub shops, bakeries, coffee shops, and pizza restaurants. In contrast, cafeterias and seafood restaurants had the lowest cumulative failure rates (Parsa et al., 2005). With the richness of my dataset, now that I know food is a significant factor, for further reference, I would like to learn more about how different cuisines impact restaurant closure by a different approach from before, by performing review analysis.

This study also enriches our understanding of the difference of sentiment positivity between open and closed restaurants' reviews. As the results suggested, reviews about food, location and service on open restaurants are generally more positive than those on closed restaurants. For future study, since determinants of business failure as well as customer reviewing are multidimensional constructs, I would also like to consider the possibility of profile scores instead of individual scores on each predictor.

As restaurant competition and failure becomes more and more prevalence these days, there is also a need to do longitudinal analysis tracking business operation over the years with continuation as an outcome. Text analysis in large amount of reviews will play a growing role in providing information about operation model for these businesses.

Limitations

This study has limitations that should be noted. First, when calculating sentiment scores, I used a built-in function from Natural Language Tool Kit called SentimentIntensityAnalyzer. Even though the function has been tested many times and been proved its accuracy, there are still discrepancies between NLTK's training model and the actual text reviews from Yelp. Further study on developing my own training model and sentiment calculating method is needed to further increase the accuracy of the outcome.

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Figure 1. *Overview of opinion summarization system*

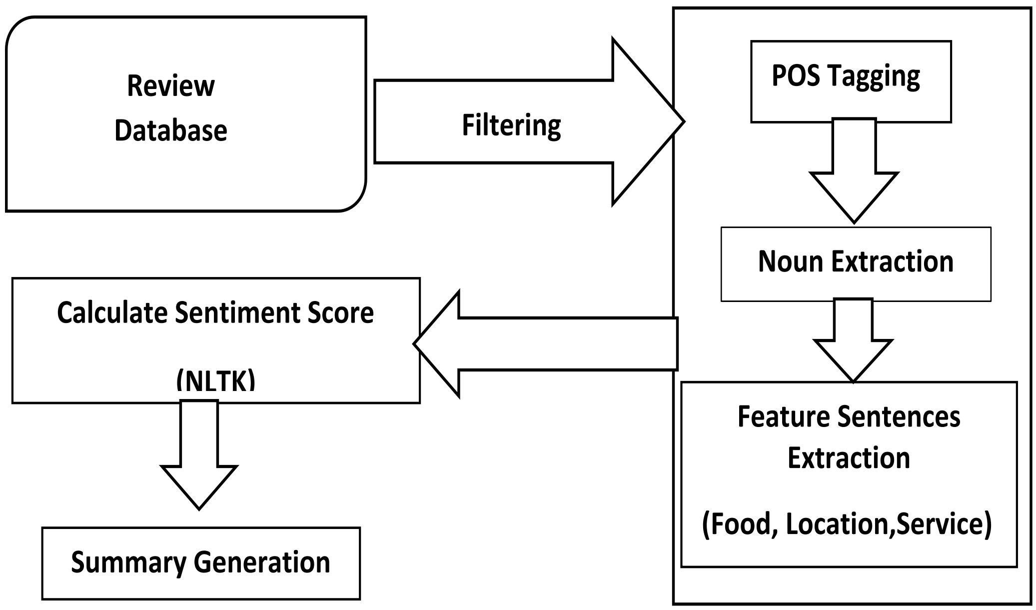

Figure 2. *Mean rating scores of restaurants*

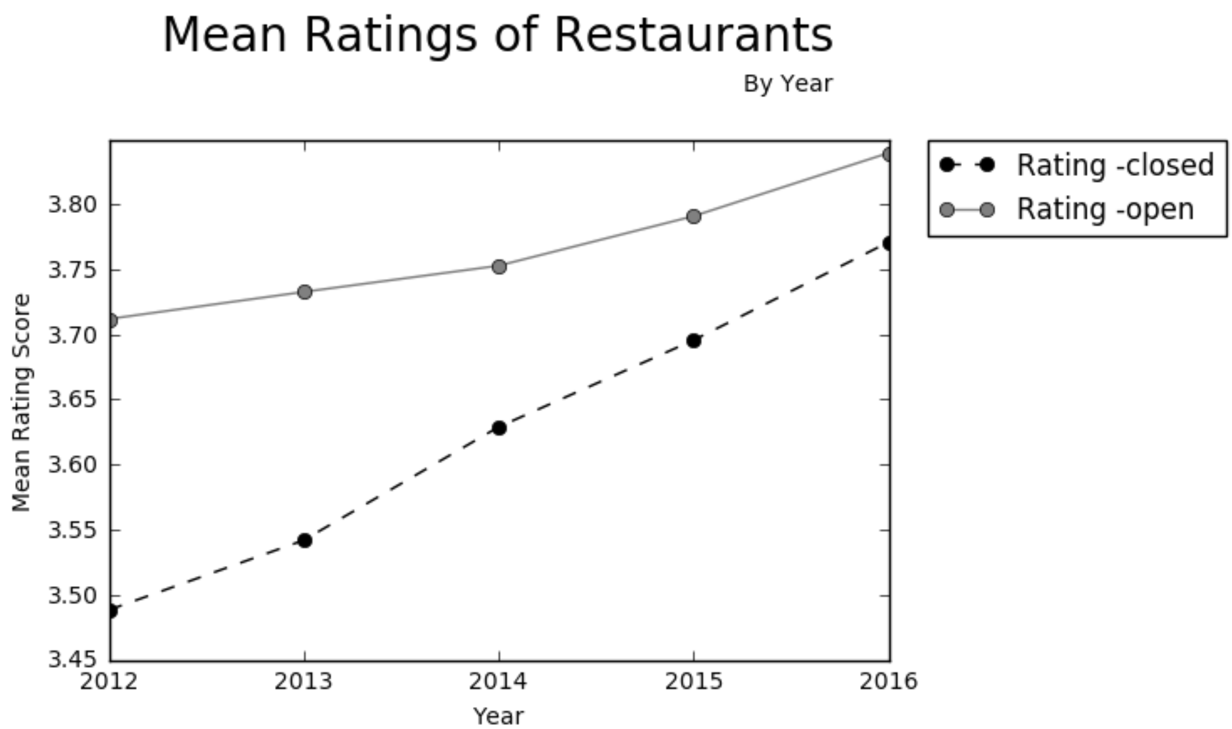

Figure 3. *Sentiment score comparisons*

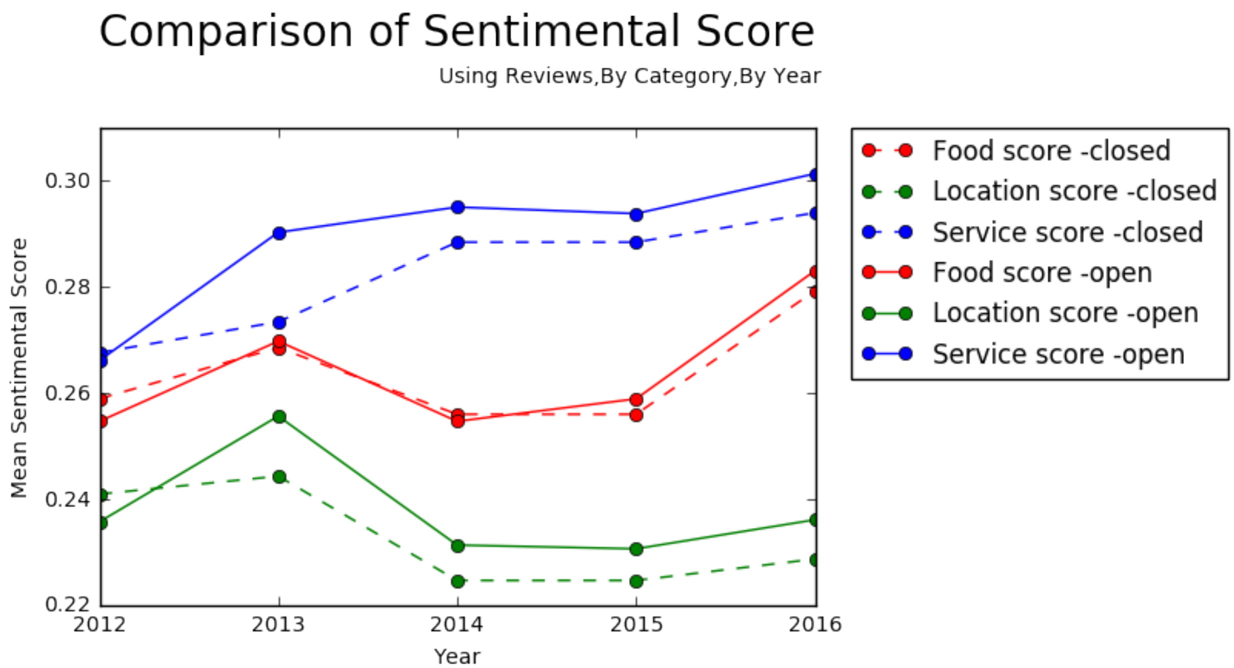

Table 1. *Descriptive statistics*

Sentiment Scores of Closed Restaurants in 2012

Statistic	N	Mean	St. Dev.	Min	Max
Food	1,289	0.167	0.204	-0.888	0.966
Location	1,289	0.156	0.224	-0.859	0.968
Service	1,289	0.173	0.283	-0.888	0.961

Sentiment Scores of Open Restaurants in 2012

Statistic	N	Mean	St. Dev.	Min	Max
Food	1,612	0.273	0.144	-0.527	0.982
Location	1,612	0.280	0.221	-0.842	0.991
Service	1,612	0.336	0.278	-0.770	0.982

Sentiment Scores of Closed Restaurants in 2013

Statistic	N	Mean	St. Dev.	Min	Max
Food	825	0.268	0.205	-0.670	0.988
Location	825	0.244	0.268	-0.820	0.988
Service	825	0.273	0.314	-0.863	0.945

Sentiment Scores of Open Restaurants in 2013

Statistic	N	Mean	St. Dev.	Min	Max
Food	2,554	0.255	0.196	-0.900	0.977
Location	2,554	0.238	0.239	-0.878	0.985
Service	2,554	0.262	0.303	-0.923	0.984

Sentiment Scores of Closed Restaurants in 2014

Statistic	N	Mean	St. Dev.	Min	Max
Food	563	0.255	0.217	-0.861	0.947
Location	563	0.224	0.258	-0.813	0.946
Service	563	0.288	0.310	-0.827	0.972

Sentiment Scores of Open Restaurants in 2014

Statistic	N	Mean	St. Dev.	Min	Max
Food	2,988	0.245	0.196	-0.885	0.954
Location	2,988	0.239	0.240	-0.933	0.982
Service	2,988	0.261	0.308	-0.902	0.982

Sentiment Scores of Closed Restaurants in 2015

Statistic	N	Mean	St. Dev.	Min	Max
Food	563	0.255	0.217	-0.861	0.947
Location	563	0.224	0.258	-0.813	0.946
Service	563	0.288	0.310	-0.827	0.972

Sentiment Scores of Open Restaurants in 2015

Statistic	N	Mean	St. Dev.	Min	Max
Food	3,446	0.241	0.187	-0.778	0.979
Location	3,446	0.238	0.238	-0.973	0.970
Service	3,446	0.268	0.295	-0.918	0.994

Sentiment Scores of Closed Restaurants in 2016

Statistic	N	Mean	St. Dev.	Min	Max
Food	310	0.278	0.237	-0.786	0.992
Location	310	0.228	0.256	-0.786	0.904
Service	310	0.293	0.310	-0.786	0.930

Sentiment Scores of Open Restaurants in 2016

Statistic	N	Mean	St. Dev.	Min	Max
Food	3,819	0.240	0.189	-0.852	0.955
Location	3,819	0.243	0.241	-0.979	0.989
Service	3,819	0.281	0.292	-0.987	0.984

Table 2. *Predictive modeling coefficients summary*

	Dependent variable
	is_open
Food	0.089***
	(0.018)
Location	0.053***
	(0.014)
Service	0.004
	(0.011)
Intercept	0.832***
	(0.005)

Note. N = 17,513. *** = $p < 0.001$.